

# Approach for forecasting smart customer demand with significant energy demand variability

Khan, Zafar; Jayaweera, Dilan

DOI:

[10.1109/ICPESG.2018.8384528](https://doi.org/10.1109/ICPESG.2018.8384528)

*Document Version*

Peer reviewed version

*Citation for published version (Harvard):*

Khan, Z & Jayaweera, D 2018, Approach for forecasting smart customer demand with significant energy demand variability. in *2018 1st International Conference on Power, Energy and Smart Grid (ICPESG)*., 45, IEEE Xplore, International Conference on Power, Energy and Smart Grid, Pakistan, 9/04/18.  
<https://doi.org/10.1109/ICPESG.2018.8384528>

[Link to publication on Research at Birmingham portal](#)

## **Publisher Rights Statement:**

Checked for eligibility: 04/06/2018

© 2018 IEEE. Personal use of this material is permitted. Permission from IEEE must be obtained for all other uses, in any current or future media, including reprinting/republishing this material for advertising or promotional purposes, creating new collective works, for resale or redistribution to servers or lists, or reuse of any copyrighted component of this work in other works

Khan, Z.A. and Jayaweera, D., 2018, April. Approach for forecasting smart customer demand with significant energy demand variability. In *2018 1st International Conference on Power, Energy and Smart Grid (ICPESG)* (pp. 1-5). IEEE.

## **General rights**

Unless a licence is specified above, all rights (including copyright and moral rights) in this document are retained by the authors and/or the copyright holders. The express permission of the copyright holder must be obtained for any use of this material other than for purposes permitted by law.

- Users may freely distribute the URL that is used to identify this publication.
- Users may download and/or print one copy of the publication from the University of Birmingham research portal for the purpose of private study or non-commercial research.
- User may use extracts from the document in line with the concept of 'fair dealing' under the Copyright, Designs and Patents Act 1988 (?)
- Users may not further distribute the material nor use it for the purposes of commercial gain.

Where a licence is displayed above, please note the terms and conditions of the licence govern your use of this document.

When citing, please reference the published version.

## **Take down policy**

While the University of Birmingham exercises care and attention in making items available there are rare occasions when an item has been uploaded in error or has been deemed to be commercially or otherwise sensitive.

If you believe that this is the case for this document, please contact [UBIRA@lists.bham.ac.uk](mailto:UBIRA@lists.bham.ac.uk) providing details and we will remove access to the work immediately and investigate.

# Approach for Forecasting Smart Customer Demand With Significant Energy Demand Variability

Zafar A. Khan\*, *Student Member IEEE*, Dilan Jayaweera, *Senior Member IEEE*  
School of Electronic, Electrical and Systems Engineering, University of Birmingham (U.K)

\*kxz511@bham.ac.uk

**Abstract**—Load forecasting in an emerging smart grid has become a challenging task. This paper presents an innovative approach to forecast highly variable smart customer load using smart meter energy consumption data. The smart meter data is systematically linearized by applying extended k-means clustering approach, smoothing the linearized load profiles and then linearizing the load profiles using Taylor series linearization process. Case studies are presented using real world smart meter data and then applying the proposed approach and artificial neural network. Four different scenarios are considered for forecasting and the results showed that, in case of high variability in smart customer energy demand, the accuracy of forecasting using linearized profiles is higher than using original non-linear profiles as the source of forecasting. The forecasting process was repeated several times to verify the robustness of the approach and the results justify the accuracy of the forecast further with the proposed approach.

**Keywords**—Artificial neural network, Load forecasting, Smart grid, Smart meter

## I. INTRODUCTION

Smart grids have introduced new technological elements like electric vehicles, prosumers, renewable energy sources (RES), advanced metering infrastructure (AMI), demand side management (DSM) [1], etc., in a power system. These elements are gradually changing the dynamics of the power system towards making it more efficient however, they enhance the challenges of the system uncertainties and complexities. One such challenge that has attracted large attention of researchers recently is load forecasting which is evident from increase in number of publications related to load forecasting [2]. Load forecasting has been part and parcel of the power system from the inception of a power system. It is crucial for planning of system expansions through examining the implications of system expansion by predicting the stress on the system components. Further, it also helps in determining the likelihood of an event which ensures correct operational planning and efficient utilization of generation resources or helping in ensuring economic load dispatch.

Prior to 1970's the demand of electricity could be anticipated easily and thus forecasting electricity demand was a simplistic process. However, the economic conditions in early 1970's forced the energy demand to change drastically which enhanced energy demand forecasting uncertainties and complexities [3]. The traditional load forecasting was limited to traditional loads whereas; the smart grids have changed the behaviour of loads. The consumers have turned into

prosumers with RES and the smart homes [4] and vehicle to grid technology [5] have changed the load patterns (frequency, magnitude, and duration) which ultimately modified the concept of conventional loads and resultant load modelling. The loads are more dynamic in nature and their interaction with system and intermittent RES is particularly multifaceted which requires different approach to forecast the loads.

Although smart grids have changed the behaviour of the loads by making them more stochastic in nature however, introduction of AMI has enabled the utility to have an insight of the consumers load behaviour. The AMI typically records energy consumption (for consumers) and/or generation (for prosumers) at 15 or 30 minutes intervals [6] and has enabled the utility to access details of individual consumers' load behaviour. The AMI has facilitated the utility by providing the details of individual consumers' load however, it has posed another challenge in the form of the big data collected by the AMI requiring data exploitation for extraction of specific knowledge. This data can potentially enable load forecasting at different horizons with significantly high accuracy at individual and system levels. Therefore, exploitation of the AMI data is of prime importance for load forecasting particularly with the consideration of the stochastic components of the load to enable a higher accuracy of a prediction.

Some of the previous studies incorporated smart meter data for load forecasting at system level. For example authors in [6] used smart meter data to forecast load based on consumer behaviour to improve the intra-day forecast accuracy. The authors used k-means clustering to cluster the data and artificial neural networks to forecast the load. However, the level of data aggregation used in the study does not help in maintaining the uniqueness of consumer patterns. With higher level of aggregation, the volatility of smart meter data is overlooked thus; impact of the individual consumers is not incorporated in reality. Kong et. al. [7] argued that prediction of load using high level aggregation of smart meter data was easier, however at a lower level, the volatility of the data becomes too high and forecasting becomes difficult. Reference [8] suggested that the variability in consumption patterns at lower level is higher and the variability of these pseudo-measurements should be understood. From the aforementioned, the key challenges that emerge from use of smart meter data for load forecasting is to determine the right level of aggregation and dealing with the volatility of the smart meter data.

This paper, presents load forecasting approach using an innovative clustering technique to determine the right level of aggregation. It introduces a novel smart meter load data modelling technique to minimize the variability while preserving the uniqueness of the energy consumption signature thus enabling the load forecasting to be more accurate. The rest of the paper is organized as following; section II describes the adopted methodology, section III delineates the numerical application and finally section IV concludes the paper.

## II. METHODOLOGY

### A. Load aggregation using clustering

The large network of AMI and smart sensors generate a large amount of data. If this data is exploited for extraction of load patterns of individual customer, this data can be utilized in decisions regarding not only the energy pricing but also for operational management which includes load forecasting. However on the other hand, getting an in-depth view of individual consumer loads for load patterns from a large volume of smart meter data is challenging with the increasing population of smart meter owned consumers [9].

To analyse smart grid data, there are different data mining and data clustering techniques. The electricity consumption data is unlabelled and stochastic in nature, the application of unsupervised learning using probabilistic techniques including data clustering is more suitable for data mining rather than deterministic techniques [10]. According to Prahastono and Ozveren [11] clustering techniques classify the consumers based on their behaviours and models of daily load profiles can be built using the classes. Therefore, data clustering can be used to identify consumers with similar energy consumption behaviours and each class of consumer can be aggregated to generate a single profile which becomes the representative profile. This profile can be used for forecasting of the entire consumer class. Most commonly used techniques for data clustering in smart grids are Hierarchical and K-means clustering. A comparative analysis of hierarchical, k-means, fuzzy c-means and two staged fuzzy clustering techniques to generated typical load profiles was carried out by [12] and it was found that K-means had the minimum MAPE while Hierarchical clustering had highest MAPE. Therefore, in this study we used extended k-means clustering which a variation of k-means clustering developed in our previous works [10, 13] and improved for automation by defining different criteria. The load profile extraction approach using clustering is given in Figure 1 (adopted from [13]). Details on the fundamentals of the developed clustering approach can be found in [13].

### B. Load modelling

Although data clustering has solved the problem of handling big data and load aggregation at suitable level, however the issue of volatility and variability of the load profiles persists. For load forecasting, variability of the data

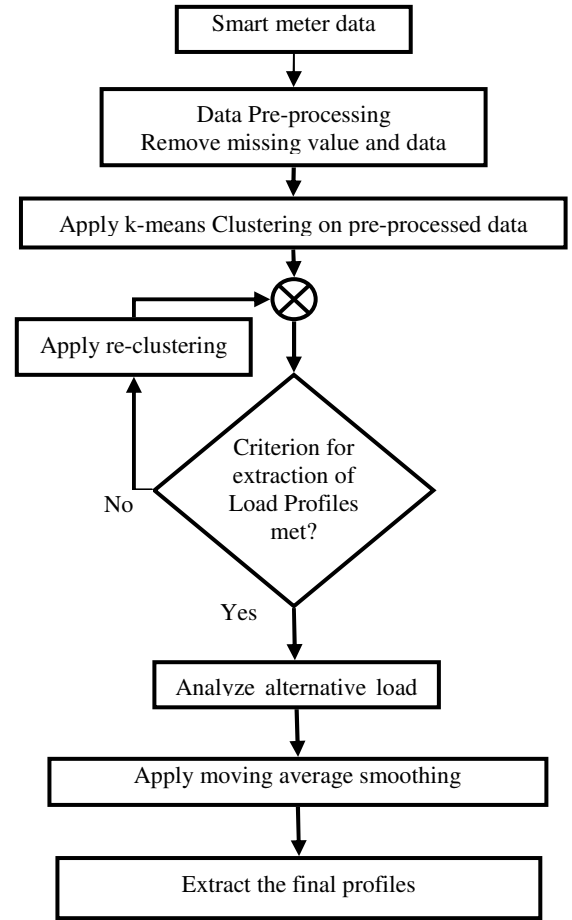


Fig. 1 Extraction of Load Profiles using extended k-means clustering (adopted from [13])

increases the uncertainty thus increasing the forecast error. This error can be tackled by linearizing the non-linear patterns thus minimizing the variations in the load over time. Linearization of load profiles from smart meter data was proposed in our previous work [10]. The improved methodology for enhanced linearization model is given in Figure 2 (adopted from [10]).

### III. NUMERICAL APPLICATION

A case study was simulated using real world smart meter data from Irish smart meter data trials [14]. The half hourly energy consumption data from more than 5000 houses was used for clustering and linearization and finally to forecast the load demand. The smart meter data used for clustering, linearization and forecasting process was for 365 days. The data clustering was performed after the pre-processing resulting in 42 clusters. These clusters were used to extract the profiles and linearize them. Figure 3 shows a profile with non-linear and linearized patterns from a cluster consisting of 53 consumers.

It can be clearly seen from the Figure 3 that the non-linear profile has a lot of variations despite the aggregation and modelling these non-linearities is a complex task. Forecasting the non-linear profile is significantly complex task but at the same time forecasting the linear profile which is an alternate of the non-linear profile with highly accurate representation of original is relatively easy. Therefore, load forecasting application can use the alternate linear load models to improve the forecasting accuracy.

Load forecasting was performed using artificial neural networks. Typically, two approaches are used for load forecasting namely, regression and time series load forecasting. The regression model considers different variables for regression but does not consider the time related outputs. The time series forecasting considers the previous outputs as input to create a forecast model. In this study, we have considered the linear regression model for development of neural network. The architecture of network was selected as a fully connected feed forward network with 10 hidden layers and each layer consisted of 20 neurons.

Some of the important choices in creating a neural network include selection of learning algorithm and activation function. All of the learning algorithms are gradient based algorithm and most commonly used algorithms are Gradient Descent and Levenberg Marquardt algorithms [15]. Lavenberg Marquardt uses gradient vector and Jacobian matrix to minimize the loss function which is sum of squared errors. However, level of calculations in this algorithm is higher than that of gradient descent and more over the ability of gradient descent to work on the graphical processing units (GPU) makes it even faster. Therefore, gradient descent learning is applied to improve the

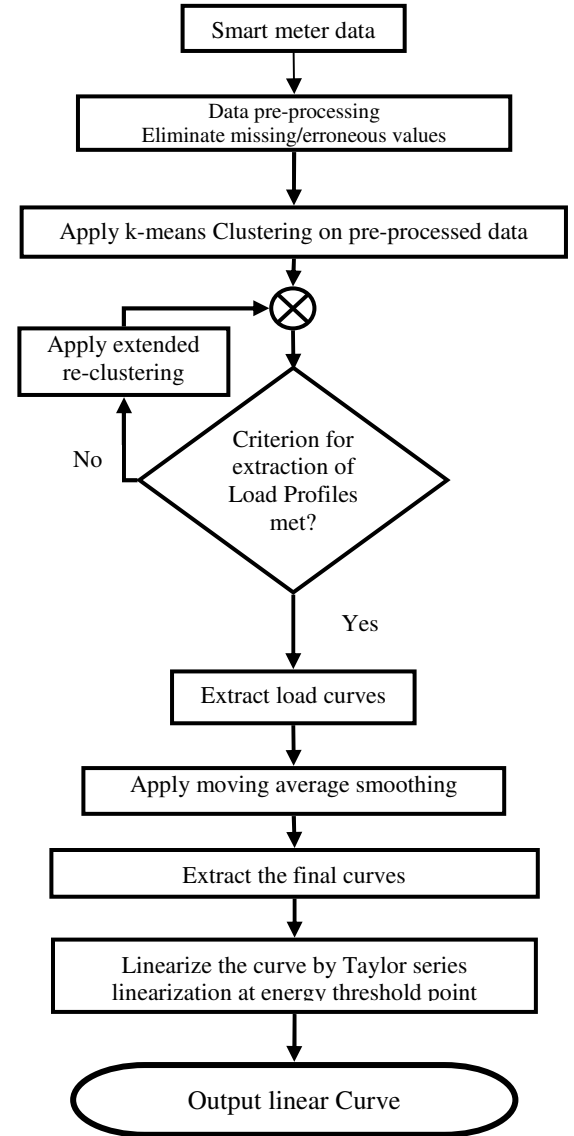


Fig. 2. Development of linear load model (adopted from [10])

forecast accuracy. The learning is carried out by back propagation algorithm where the gradient of the cost function is calculated and propagated back to the first hidden layer. The weights and biases are adjusted in accordance to the deltas calculated from the gradients.

Sigmoid activation function is commonly used in neural networks for regression purposes however, due to the problem of vanishing gradient; they are avoided in deep neural networks. An alternative to the sigmoid for deep learning is rectified linear units (ReLU) function, but empirical evaluation in our case study revealed that sigmoid produced better accuracy than ReLU with network being shallow.

Half energy consumption hourly data of 365 days was used to train the neural network. To verify the accuracy of forecast, load samples for one-week which were not included in the training data were used. Training data sets were divided into two different categories namely linear and non-linear. The prediction variables used in this study included;

- Weather variable
  - Temperature
- Calendar variables
  - Day of the week
  - Hour of the day
  - Holiday
- Load variables
  - Previous day same hour load
  - Previous week same hour load
  - Average load of previous 24 hours.

After selecting the variables, two types of training data were used. Firstly, the original non-linear data was used to train the neural network. Secondly the data used to train neural network, particularly the load variables were extracted from the linearized load profiles. Thus, the training performed was using the linearized profiles in second case.

Four different clusters were selected for the forecast accuracy assessment. Selection of clusters was driven by the

level of aggregation which in terms reflects the variability. The selected profiles were representative of 70, 121, 411 and 796 consumers. To ensure the fairness in evaluation of both profiles, each profile was trained and tested multiple times and the best results were noted. The results of forecast are given in table 1. The comparative forecasted load curves for both linear and non-linear profiles for two clusters are given in Figure 4.

The accuracy of forecast is quantified using three measures, i.e. mean absolute percentage error (MAPE), mean absolute error (MAE) and daily peak MAPE. The results suggest that with low number of consumer, the variability often tends to be high (as can be seen from Figure 4), in such cases the linear profiles perform better than the non-linear profiles. In first two cases, the number of consumers was quite low which resulted in linear profile performing better than the non-linear ones. An important aspect of the results is that the linear profile training took more time than the non-linear ones. This is possibly a result of learning process of the non-linear profiles, getting stuck in local minima which is also reflected in the accuracy.

On the contrary, in clusters with high number of consumers, the forecast of non-linear profiles outperformed the linear profiles forecast. Reduced variability in the profiles due to the high number of consumer is a significant contributing factor in improved accuracy. The loss in accuracy for the linear model results from the loss in the process of linearization. Despite the loss, the overall gain in accuracy in linear profiles is higher than the overall loss.

From the above results, it can be seen that the linearized

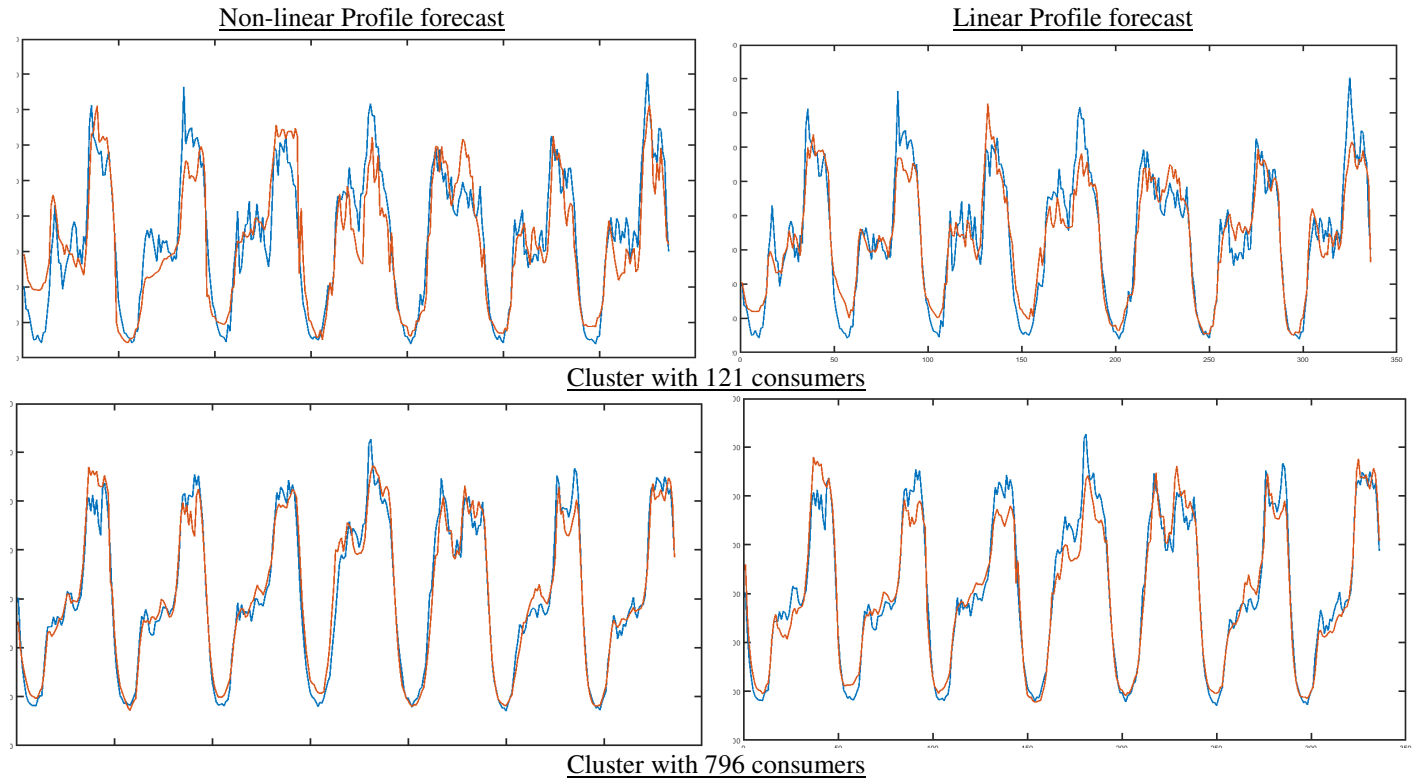


Fig. 4. Forecast generated by non-linear and linear profiles (Blue line shows the target and red line shows the forecast)  
 X-axis show 0.5 hourly steps (0-336) and Y-axis show Load (kWh)  
 (X-axis shows time in hours and Y-axis shows load in kWh/30 mins)

Table 1: Errors in load forecasting using non-linear and linear profiles

No. of Customers in a cluster		70	121	411	796
Mean absolute percentage error (MAPE)	Non-linear Profile	9.88%	16.35%	7.75%	5.85%
	Linear Profile	8.9%	12.72%	8.08%	6.41%
Mean absolute error (MAE)	Non-linear Profile	7.92 kWh	12.75 kWh	14.86 kWh	22.93 kWh
	Linear Profile	7.31 kWh	9.54 kWh	17.31 kWh	26.29 kWh
Daily peak MAPE	Non-linear Profile	5.39%	7.41%	6.19%	4.31%
	Linear Profile	4.27%	10.94%	8.05%	5.63%

load model performs better than that of the non-linear models in cases where the variability in the data is high. The proposed approach for load forecasting can significantly benefit in improving the data handling, reducing the complexity of the data and improving the forecast accuracy in spite of the highly volatile data.

#### IV. CONCLUSION

This paper proposed an innovative approach for smart meter customer load forecasting by restructuring the non-linear energy meter profiles into linearized profiles. The robustness of the approach was justified using highly variable smart meter customer demand data.

The case study justified the value of using the proposed approach against the neural networks, in particular with highly variable smart meter customers' demands. The aggregation of the cluster forecast proved to provide a more accurate forecast while preserving the volatility of the data.

Approach can be incorporated into the planning and operation of smart power systems where the active customer participation is highly volatile due to habitual patterns, multitudes of active customer owned business models, and prosumer operation.

#### REFERENCES

- [1] Z. A. Khan, S. Ahmed, R. Nawaz, A. Mahmood, and S. Razzaq, "Optimization based individual and cooperative DSM in Smart Grids: A review," in *Power Generation System and Renewable Energy Technologies (PGSRET)*, 2015, 2015, pp. 1-6.
- [2] Y. Loewenstern, L. Katzir, and D. Shmilovitz, "The effect of system characteristics on very-short-term load forecasting," in *2015 International School on Nonsinusoidal Currents and Compensation (ISNCC)*, 2015, pp. 1-6.
- [3] P. S. Leung and W. Miklius, "Accuracy of electric power consumption forecasts generated by alternative methods: the case of Hawaii," *Energy sources*, vol. 16, pp. 289-299, 1994.
- [4] W. Young-Min, L. Jong-uk, and J. Sung-Kwan, "Electric vehicle charging method for smart homes/buildings with a photovoltaic system," *Consumer Electronics, IEEE Transactions on*, vol. 59, pp. 323-328, 2013.
- [5] B. Chen, K. S. Hardy, J. D. Harper, T. P. Bohn, and D. S. Dobrzynski, "Towards standardized Vehicle Grid Integration: Current status, challenges, and next steps," in *Transportation Electrification Conference and Expo (ITEC)*, 2015 IEEE, 2015, pp. 1-6.
- [6] F. L. Quilumba-Gudino, "Using Advanced Metering Infrastructure Data For Smart Grid Development," 2014.
- [7] W. Kong, Z. Y. Dong, Y. Jia, D. J. Hill, Y. Xu, and Y. Zhang, "Short-Term Residential Load Forecasting based on LSTM Recurrent Neural Network," *IEEE Transactions on Smart Grid*, vol. PP, pp. 1-1, 2017.
- [8] R. Sevlain and R. Rajagopal, "Short term electricity load forecasting on varying levels of aggregation," *arXiv preprint arXiv:1404.0058*, 2014.
- [9] A. M. Ahsan Raza Khan, Awais Safdar, Zafar A. Khan, Naveed Ahmed Khan, "Load forecasting, dynamic pricing and DSM in smart grid: a review," *RENEWABLE AND SUSTAINABLE ENERGY REVIEWS*, 2015.
- [10] Z. A. Khan and D. Jayaweera, "Approach for smart meter load profiling in Monte Carlo simulation applications," *IET Generation, Transmission & Distribution*, vol. 11, pp. 1856-1864, 2017.
- [11] I. Prahastono, D. King, and C. S. Özveren, "A review of electricity load profile classification methods," in *Universities Power Engineering Conference, 2007. UPEC 2007. 42nd International*, 2007, pp. 1187-1191.
- [12] Y.-I. Kim, S.-J. Kang, J.-M. Ko, and S.-H. Choi, "A study for clustering method to generate Typical Load Profiles for Smart Grid," in *Power Electronics and ECCE Asia (ICPE & ECCE)*, 2011 IEEE 8th International Conference on, 2011, pp. 1102-1109.
- [13] Z. Khan, D. Jayaweera, and H. Gunduz, "Smart meter data taxonomy for demand side management in smart grids," in *Probabilistic Methods Applied to Power Systems (PMAPS)*, 2016 International Conference on, 2016, pp. 1-8.
- [14] "CER Smart Metering Project - Electricity Customer Behaviour Trial, 2009-2010, Accessed via the Irish Social Science Data Archive - [www.ucd.ie/issda](http://www.ucd.ie/issda)," ed.
- [15] D. W. Marquardt, "An algorithm for least-squares estimation of nonlinear parameters," *Journal of the society for Industrial and Applied Mathematics*, vol. 11, pp. 431-441, 1963.